

## Reconstruction of an Infrared Band of Meteorological Satellite Imagery with Abductive Networks<sup>1</sup>

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### Abstract.

As the current fleet of meteorological satellites age, the accuracy of the imagery sensed on a spectral channel of the image scanning system is continually and progressively degraded by noise. In time, that data may even become unusable. We describe a novel approach to the reconstruction of the noisy satellite imagery according to empirical functional relationships that tie the spectral channels together. Abductive networks are applied to automatically learn the empirical functional relationships between the data sensed on the other spectral channels to calculate the data that should have been sensed on the corrupted channel. Using imagery unaffected by noise, it is demonstrated that abductive networks correctly predict the noise-free observed data.

### 1 Introduction.

The fleet of four polar orbiting meteorological satellites currently operated by the National Atmospheric and Oceanic Administration (NOAA) carries a multi-spectral sensing system for imaging the Earth. This system, the Advanced Very High Resolution Radiometer (AVHRR), measures irradiances in five narrow spectral bands ranging from the visible to the infrared (IR) parts of the electromagnetic spectrum. The system is described in section 2 below. Suffice it to say here that by virtue of the high resolution of the instrument, a wealth of data is available.

It has been noted that one of the five spectral channels of the AVHRR (channel 3) is particularly susceptible to noise and its accuracy degrades with age, perhaps to the point where the data is unusable (Ref. 1). The possibility also exists that some of the archived AVHRR imagery from the older satellites that have been replaced with the current generation of spacecraft may also be of questionable quality.

The problem faced is the use of archived and real-time satellite imagery which may be partially corrupted by noise. One approach is to correct the data to its true but *a priori* unknown value. Because the channel is continually and progressively denigrated by noise, any correction scheme requires constant maintenance.

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An alternative approach, pursued in study described here, is to replace the data measured on the noisy channel with data constructed from the other four spectral channels. Our approach relies on a technique called abductive networks that automatically discovers the networking between the spectral channels that are embedded in the measured data. In this way the noisy satellite imagery is reconstructed according to empirical functional relationships that tie the spectral channels together.

Here we describe the application of a proprietary tool for creating abductive networks to the modelling of the AVHRR. Specifically, channel 3 is modelled as the output calculated from the empirical inputs of the other four spectral channels. Our approach was exercised on imagery collected with the AVHRR on NOAA-11, which is not as yet seriously compromised by noise. The data predicted for channel 3 with the other channels as inputs to the network that was created is then statistically compared to the data actually observed. The result was that the network was highly successful at simulating the observed output.

The next section provides a short description of the AVHRR. Section 3 gives an overview of abductive technology. Section 4 describes the application of abductive networks to satellite imagery with the objective of uncovering the effective relationship between the imagery sensed in an intermediate spectral band and the imagery sensed in the neighboring bands. Our conclusions, principally that abductive networks show great promise for reconstructing noisy satellite imagery, are presented in section 6.

## 2 A Brief Description of the AVHRR.

The AVHRR currently flown aboard the NOAA polar orbiting meteorological satellites is a downward-pointing cross-track scanning system. It makes radiometric measurements in five spectral channels: two in the visible and adjacent near-infrared (near-IR) part of the spectrum (channels 1 and 2) and three in the IR part (channels 3, 4, and 5). The spectral band widths, in microns ( $\mu\text{m}$ ), are summarized in Table 1. For NOAA-10 only, the spectral band of channel 4 is 10.50 - 11.50  $\mu\text{m}$ , and channel 5 output is a repeat of channel 4. The field of view of each channel is approximately 1.4 milliradians leading to a nadir resolution of about 1.1 km (for a nominal satellite altitude of 833 km). There are 2048 pixels per scan line, where each pixel covers about 2 steradians.

Table 1. Spectral band widths of the AVHRR.

Channel #	Band Width ( $\mu\text{m}$ )
1	0.580 - 0.680
2	0.725 - 1.100
3	3.550 - 3.930
4	10.300 - 11.300
5	11.500 - 12.500

The analogue data output from the sensors is digitized on board the satellite. The IR channels are calibrated in flight using a view of a stable black body and space as a reference. No in flight visible channel calibration is performed, although the space view is available as a reference point.

The radiometer data collected by channel 3 of each NOAA satellite have been very noisy due to sensor problems and may be eventually unusable (Ref. 1). This is especially true when the satellite is in daylight. (Of course, channels 1 and 2 are blank for nocturnal views.)

The normal operating mode of the AVHRR scanning system is to capture a scan line in a buffer and continuously broadcast the digital data in a wide beam aimed at the Earth. The direct transmission mode is called High Resolution Picture Transmission (HRPT). Ground processing of the HRPT consists of its calibration, earth location, and breakout of the individual sensor channels.

### **3 An Introduction to Abductory Induction and Abductive Networks.**

Abductive reasoning, or abduction, is defined as the process of reasoning under conditions of uncertainty from general principles and initial facts to new facts (Ref. 2). Abduction differs from deduction, in which all principles and facts are assumed to be known with complete or assumed certainty.

Induction is the process of reasoning from specific facts to general principles. This reasoning process handles the many real-world situations that are rich in empirical data but lack sufficient conceptual understanding to unify that data into a coherent, accurate view of the world. Ideally, the facts supplied to an inductive argument are known with absolute certainty. In the real world, however, the facts are contaminated with uncertainties. Uncertainty arises, for example, from imprecise, unreliable or incomplete information. Even with indisputable information, uncertainty arises due to a lack of complete and thorough knowledge and understanding of the situation. Then the generalities inductively reasoned from those facts must themselves be uncertain. As a result, the reasoning itself contains uncertainty. Abduction is the reasoning process that incorporates this realistic view of uncertainty.

A practical implementation of abductive reasoning uses numeric functions and measures, called abductive measures, to convey the inherent importance of a single fact or piece of information (Ref. 2). Abductive measures represent relationships between facts. These should be viewed as working, rather than 'true', relationships in the sense that they predict nature correctly even if for the wrong reasons.

Abductive measures are used to decompose complex problems into subproblems in a process called chunking. Here a limited number of facts, or types of facts, are dealt with at a time. They are summarized in terms of single abductive measures. The chunks are then united by appropriately combining their respective abductive measures.

Abductory induction is the process of creating general principles from databases of empirical observations. Abductory induction is applied to create an abductory model of the process

described implicitly by the database by formulating, or at least approximating, the relationship between the database variables in terms of the contained data. The abductory model is most conveniently posed as an unstructured network or a cascade of mathematical equations. This adaptability property makes abductory induction particularly well suited to unsupervised machine learning. The problem immediately posed is determining the appropriate functions, and hence the layout of the network, out of an infinite number of candidates, that best describes the data. Assuming a model structure, as is done in regression techniques, may result in poor fits to the data just because that specific structure is not present. An alternative is to model the data with a very general multinomial. Within very broad assumptions any arbitrary function may be approximated by a polynomial (i.e., a truncated Taylor series); the accuracy of the approximation is directly related to the number of terms retained, that is, the degree of the polynomial. However the many coefficients needed for even a small set of variables makes this approach intractable for degrees much above 2.

A practical solution to modelling the database in terms of its uncertain structure is to apply the chunking concept and split the input variables among several groups. The groups are collectively input to the individual nodes of an incipient network and the relations among them are summarized in terms of an abductive measure. These results are then passed on to the next layer of the evolving network. The labor is substantially reduced because only the model associated with a single node must be determined at any single time.

Abductive networks are networks of functional nodes (Ref. 3). Neural networks may be considered a special class of biologically-motivated abductive networks. Incorporating the chunking concept, a very effective algorithm for creating abductive networks utilizes polynomial equations (of moderate order) for the abductive measures. Given a database of example situations about a problem consisting of a representative set of inputs and outputs, an abductive network can be used to fit the best polynomials relating the variables, node by node, cascading layer to layer. Specifically, inputs to each node are processed and output, along with the original input variables to the nodes in subsequent layers of the network. The result is a compact representation of the interactions between the variables as evidenced in the massive amount of empirical data.

The Abductory Induction Mechanism (AIM™) is proprietary software of AbTech Corporation for implementing abductory induction for the automatic and unsupervised creation of abductive networks (Ref. 4). The network created by AIM is a robust and efficient representation of the relationships existing between the variables contained in the database. AIM uses polynomials of up to degree 3; the polynomials contain cross-terms to allow interaction between node inputs. Not all terms may be included in specific nodal polynomials because AIM, in a process called carving, neglects terms which do not contribute significantly. The network size, chunking and connectivity (between chunks and/or inputs), and coefficient values are all determined automatically by AIM. Networks are created from layer to layer until the network model ceases to be improved according to a modeling criterion. The criterion assures that as accurate a network as possible is created without overfitting the data (that is, tailoring the network specifically to the supplied database).

#### **4 An Application of AIM to the AVHRR Calibrated Channel Output.**

It was mentioned above that, for the older satellites in the NOAA fleet, channel 3 is very noisy, to the point of being unusable without significant suppression of the noise effects. The objective is to reconstruct channel 3 from the other four spectral channels.

The AVHRR instrument scans the scene pixel by pixel in all five spectral channels simultaneously. Of course, the sensors will make different irradiance measurements in the different spectral bands. However, in a pixel, excluding any possible misalignment among the five fields of view, the channel 3 irradiance must be related to the irradiances measured on the other spectral channels. That relation is a complex problem in radiative transfer for both solar and terrestrial photons. An alternative to a possibly intractable theoretical analysis is to use a satellite imagery database consisting of AVHRR calibrated output to uncover empirical relationships between channel 3 and the other channels contained in the data.

The SAIC satellite ground station at received imagery from the NOAA-11 satellite for a pass over the eastern United States on 25 February 1994 around 2139 UTC (16:39 EST). NOAA-11 was launched September 24, 1988; as the second oldest satellite in current operation, it is two years older than NOAA-10 and nearly four years older than NOAA-9. The AVHRR on NOAA-11 has not yet evidenced severe denigration of any of its spectral irradiance measurements. The downlinked data was calibrated, rectified, and broken out into its individual channels, which were separately saved to file. The satellite image contained in excess of 1000 scan lines. A 500 line by 500 pixel box was extracted from the southwest corner of the image and sampled for every other scan line, so that the channel databases each contained 250 scan lines nominally separated by 2.2 km in the direction of the satellite track. The data for each individual channel were then ordered by pixel, for a total of 125000 pixels, in a single file for each of the five channels. Each pixel is considered as an individual observation containing five values, one for each of the spectral channels.

The AIM software package was applied to the image box. Memory limitations in AIM prevented use of the entire database because AIM is limited to only 8000 observations. As a result, four 8000-pixel strips were extracted from the image box. Specifically, the extracted image box was divided into four sections in the along-track direction. Each section of the image box was sampled in blocks of 8000 pixels such that each block contains sixteen sequential 500-pixel neighboring scan lines; the blocks are spatially coherent. A fifth block was created by assembling four adjacent scan lines from each of the four image strip. Note that while the quarters of this image block are spatially coherent, the quarters are spatially decoupled from each other.

Channels 1, 2, 4, and 5 were designated as the network inputs and channel 3 was designated as the network output. Individual networks were created for each of the five image blocks. The networks were created on a Macintosh SE/30. The time required for forming the network obviously depended on network complexity. Creation times ranged from about 20 minutes up to nearly an hour. Each network was then evaluated against both its own creating image block and the other four image blocks. The evaluation consisted of statistically comparing the channel 3

output predicted by the network to the channel 3 data actually observed.

All of the networks performed well on self-evaluation. Generally the networks degraded with spatial distance of the evaluating image block from the network-forming image block, that is, with progressive spatial decoupling between the image blocks. The exception was the AIM network created with image block 5 (the four-strip composite through the 500 line by 500 pixel image box). That network, presented in figure 1, generally outperformed all the other networks, except for their own self-evaluation.

As can be seen in figure 1, the network created with image block 5 is a four-layer network of feed-forward elements, that is, the network cascades from the raw input variables on the left to the single output variable on the right. The inputs are the calibrated AVHRR data from channels 1, 2, 4, and 5. Note however that only channels 1, 4, and 5, referred to as ch1, ch4, and ch5, respectively, were used. The final output is the network-predicted (calibrated) response for AVHRR channel 3, referred to as ch3. Channel 2 was carved from the inputs because of its partial redundancy, most likely with channel 1. The numbers and types of network elements, the element polynomial functions, and their connectivity are learned abductively (induction under uncertainty). The coefficients of the element functions are determined by multiple linear regression of terms up to power three. The structure of the network is determined according to a set of rules and heuristics that are an inherent part of the AIM network creation strategy. The best network, in terms of its structure, element types, coefficients, and connectivity, is found automatically by minimizing a modeling criterion that seeks the most accurate network possible within acceptable tolerance (this avoids creating a network tailored to only the training data).

In figure 1, the open circles following the inputs are 'normalizers'. They transform the the original input variables to standard variables with zero mean and unit variance. This assures that all input variables will be fairly represented in the network. The boxes labelled double and triple are elements whose name is based on the number of inputs from the previous layer. These elements are described by fairly general third-order polynomials. Doubles and triples may have some significant explicit cross-product terms, allowing interaction among the node input variables. Note that the output of any given element can feed subsequent layers as can the original variables. The open circle preceding the network output (ch3) is a so-called 'unitizer'. A unitizer converts the standardized range of the intermediate network output to the units of the output variable used to create the network; it is an inverse normalizer.

Figure 2 plots the observed output of channel 3 in image block 5 against the output predicted for channel 3 using the data measured on the other channels in block 5 as input to the network created with block 5. This is a self-evaluation of the network created with image block 5. The line with unit positive slope indicates perfect correlation between the observed and the predicted channel 3 output. The overwhelming bulk of the 8000 network-predicted channel 3 values straddle the line, indicating the high quality of the network fit to the observations. The correlated data appear to group predominantly into two large clusters hugging the unit line (the upslope cluster being the more massive of the two). Apparently the observed channel 3 data is inherently bimodal; this bimodal distribution is captured in the network predictions. Figure 3 displays the normalized errors for this self evaluation of the block 5 network. Normalized error is defined as

the difference between the observed and predicted values for the channel 3, normalized by the observed value. As in the previous figure, the normalized errors group predominantly into two large clusters hugging the zero-error line. The larger of the two clusters sits over the mean of the channel 3 observations for block 5 (2324.3). The normalized errors are mainly within  $\pm 5\%$ , and nearly evenly dispersed around the zero-error line. As the observed values depart from the block mean, error grows, implying that the network performance degrades. Even at its worst, however, the normalized error is mostly within about 15%.

Figure 4 plots the observed output of channel 3 in image block 3 against the output predicted for channel 3 using the data measured on the other channels in block 3 as input to the network created with block 5. The perfect correlation line with unit positive slope is displayed for comparison. Here, the agreement between the predicted and the observed values is excellent, as evidenced by the near perfect collapse onto the  $45^\circ$  line. The normalized errors between the block 5 network predictions of channel 3 for block 3 and the actual block 3 observations are shown in figure 5. The normalized errors are strongly clustered about the actual block mean of 2316.9, and are about 1%. Note that in general the network tends to very slightly overpredict the channel 3 output. The strong clustering of the normalized errors reflects the shorter range and tighter clustering of the block 3 data about its mean (standard deviation = 27.0 ~ 1.2% of the mean).

## 5 Conclusions.

We have demonstrated that that abductive networks are very successful in modelling the measurements collected with the AVHRR in our specific test case. The abductive networks created with AIM create reliable and compact representations of the AVHRR spectral channels in terms of diagnosing the empirical relationship between channel 3 and the other four spectral channels. The network trained with the composite database selectively extracted from the imagery so as to have only partial spatial coherence generally outperformed the networks trained with spatially coherent databases, except perhaps for the self-evaluation. This indicates some near-universality exists in the relationship between the channels, which may be found by the appropriate sampling of the satellite imagery. The general use of abductive networks for modelling the AVHRR towards reconstructing the noisy data collected on its channel 3 shows great promise.

Another possible use for abductive networks is as a quality-control monitor. Specifically, the real-time degradation of channel 3 can be measured by periodically comparing its observations to network predictions. For example, the channel may be considered corrupted if the average error, say, between the observed and the predicted channel 3 output through an image (or a piece of an image) exceeds some established threshold.

## 6 References.

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4. AIM Users Manual, Macintosh version 1.0, AbTech Corporation, Charlottesville, VA, 1990.



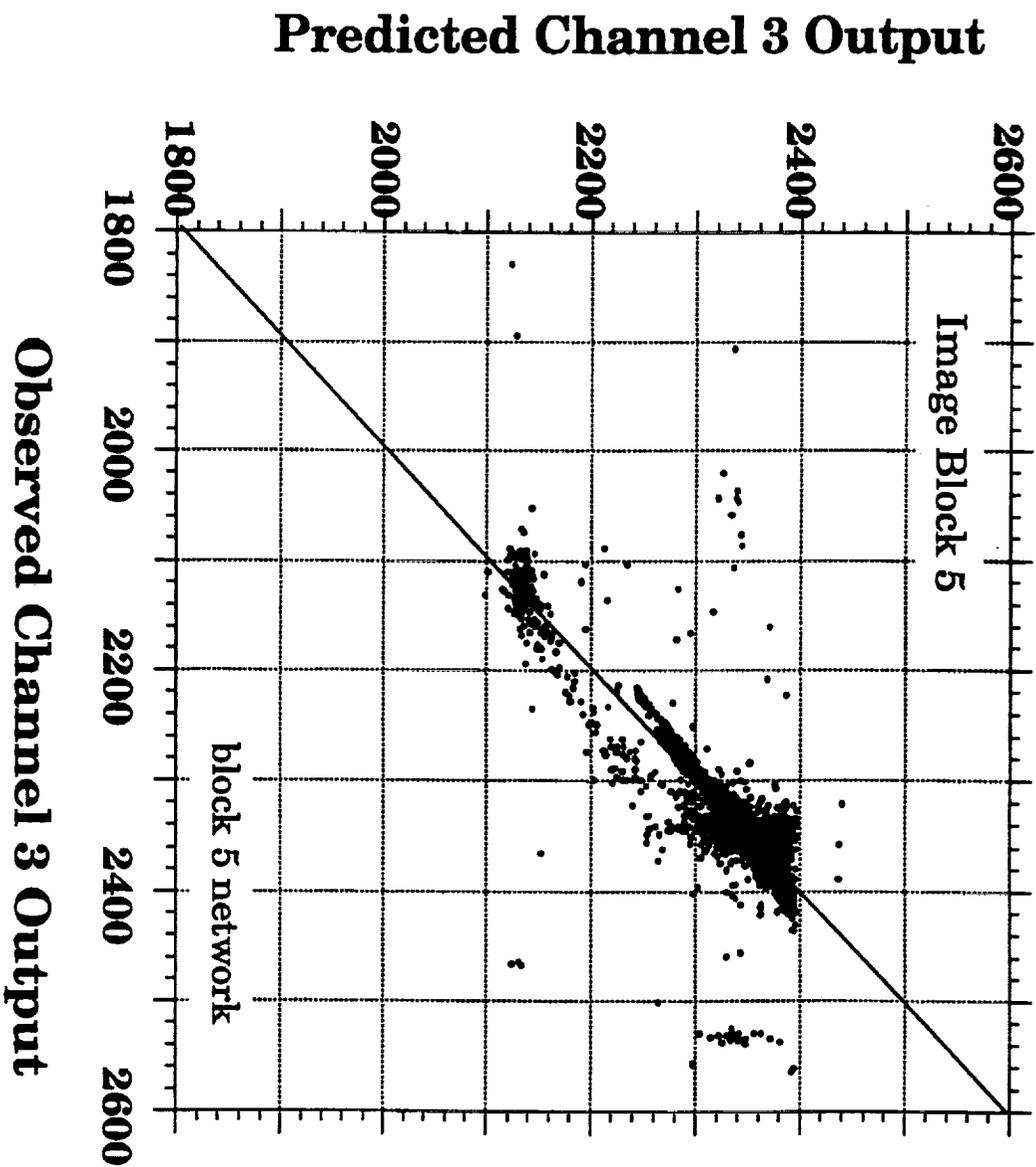


Figure 2. Observed channel 3 output in image block 5 vs. the predicted output using the other block 5 channels as inputs to the network created with image block 5.

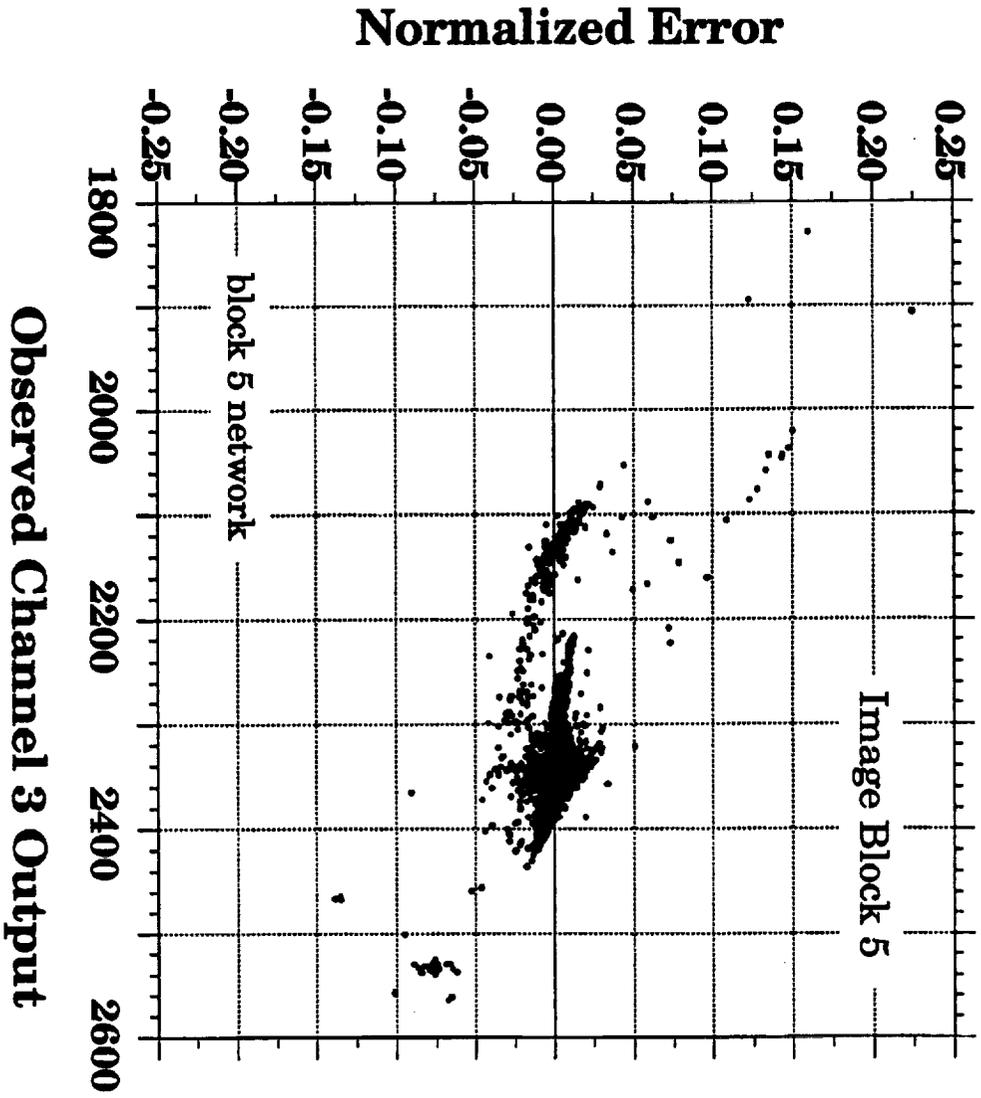


Figure 3. Normalized channel 3 output errors in image block 5, between the observed output and the output predicted from the network created with image block 5.

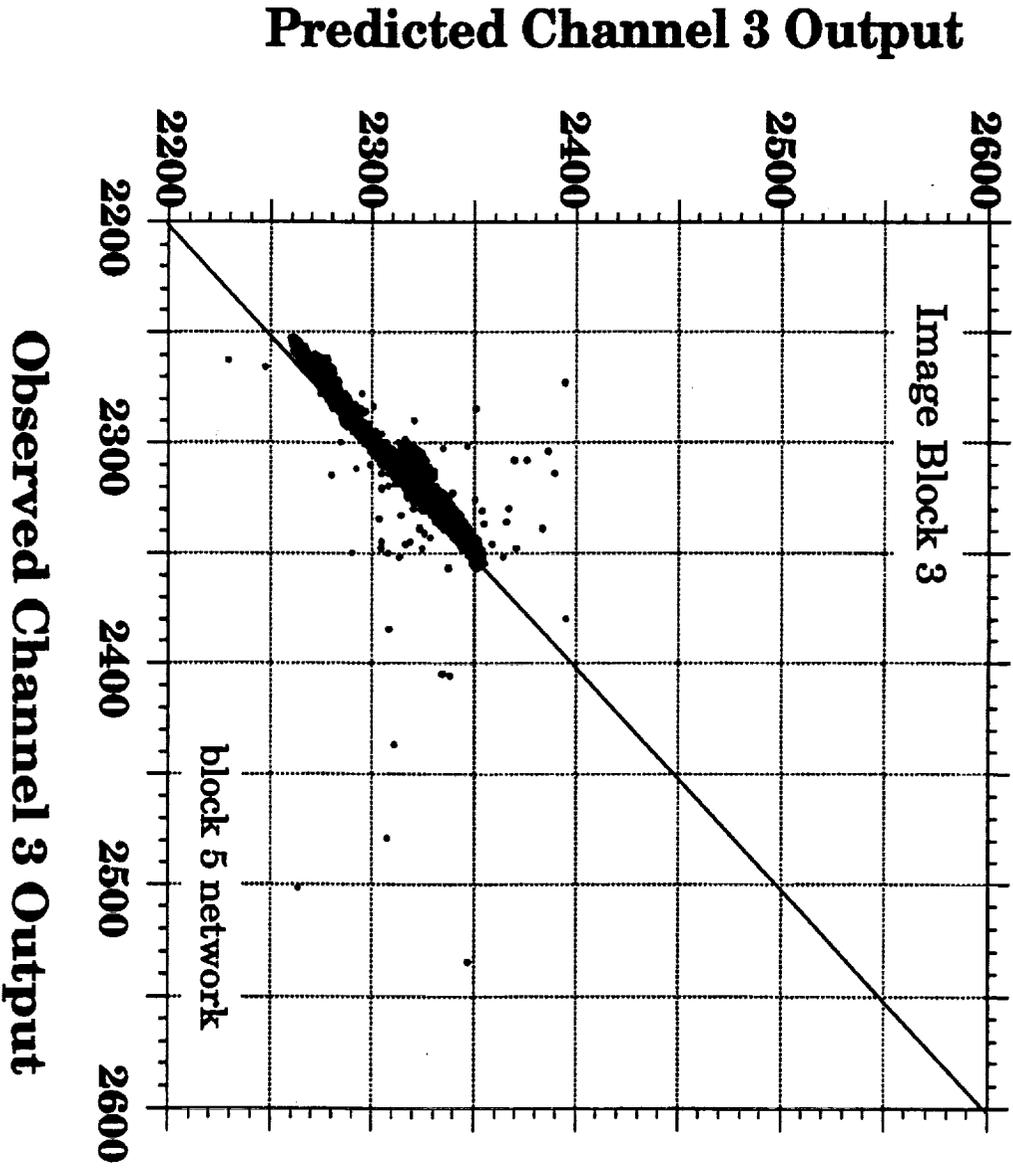


Figure 4. Observed channel 3 output in image block 3 vs. the predicted output using the other block 3 channels as inputs to the network created with image block 5.

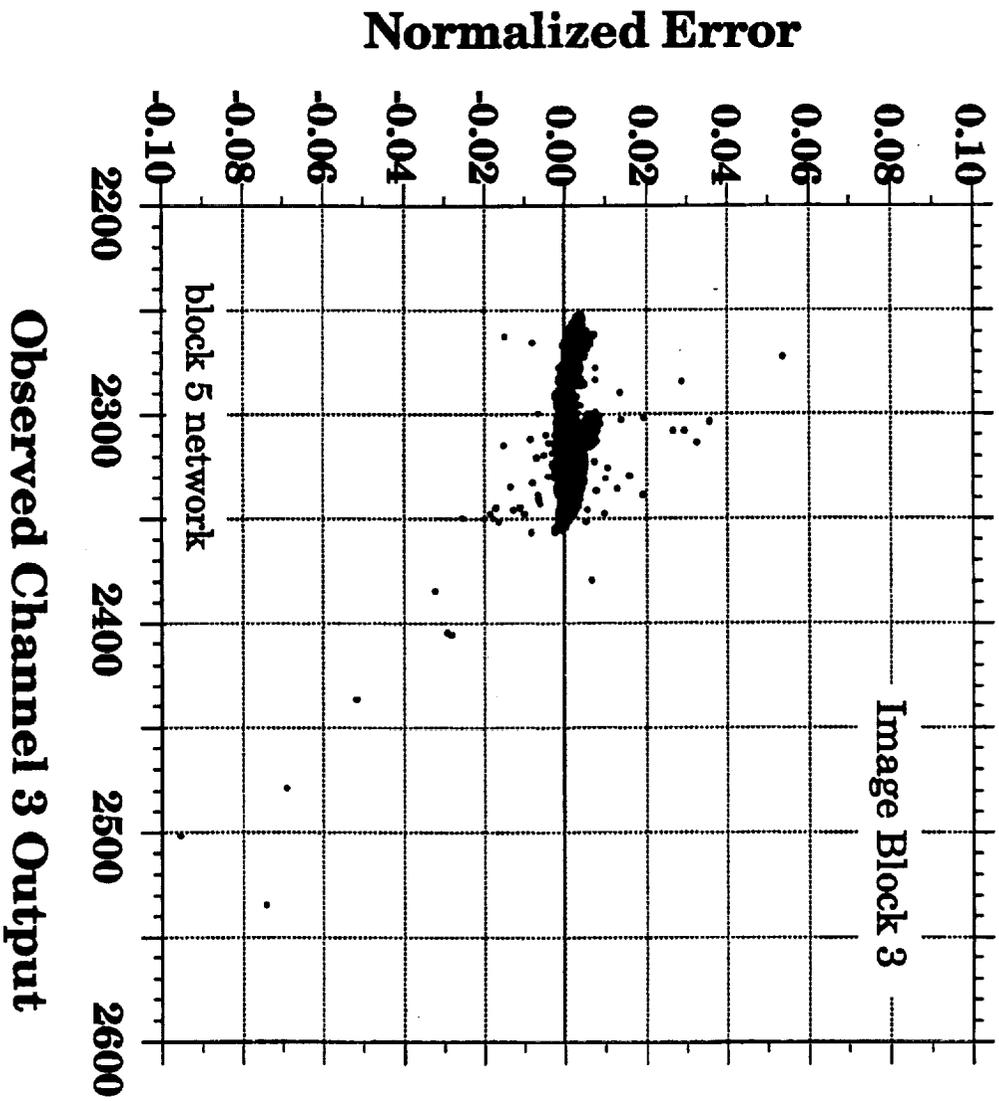


Figure 5. Normalized channel 3 output errors in image block 5, between the observed output and the output predicted from the network created with image block 5.

